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Research Article

An Examination of Strategy Implementation During Abstract Nonlinguistic Category Learning in Aphasia

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Purpose: Our purpose was to study strategy use during nonlinguistic category learning in aphasia.
Method: Twelve control participants without aphasia and 53 participants with aphasia (PWA) completed a computerized feedback-based category learning task consisting of training and testing phases. Accuracy rates of categorization in testing phases were calculated. To evaluate strategy use, strategy analyses were conducted over training and testing phases. Participant data were compared with model data that simulated complex multi-cue, single feature, and random pattern strategies. Learning success and strategy use were evaluated within the context of standardized cognitive–linguistic assessments.
Results: Categorization accuracy was higher among control participants than among PWA. The majority of control participants implemented suboptimal or optimal multi-cue and single-feature strategies by testing phases of the experiment. In contrast, a large subgroup of PWA implemented random patterns, or no strategy, during both training and testing phases of the experiment.
Conclusions: Person-to-person variability arises not only in category learning ability but also in the strategies implemented to complete category learning tasks. PWA less frequently developed effective strategies during category learning tasks than control participants. Certain PWA may have impairments of strategy development or feedback processing not captured by language and currently probed cognitive abilities.

For decades, cognitive neuroscientists have explored probabilistic category learning tasks to better understand learning systems in healthy and clinical populations (for review, see Ashby & Maddox, 2005). Categorization allows us to organize stimuli and integrate information on the basis of commonalities. This is a critical skill that underlies our ability to rapidly recognize and assign meaning to experiences in the context of infinite environmental stimuli and scenarios. Humans must constantly, and fluidly, classify novel items into discrete categories such as large or small, friend or foe (for review, see Maddox, 2002; Seger & Miller, 2010), with some theories proposing that this ability to categorize at least partially underlies our ability to form concepts (Palmer, 2002; Waxman & Gelman, 2009; Zentall, Galizio, & Critchfield, 2002). Research has examined many types of category learning—which include category tasks learned through logic that can be prescribed as well as category tasks requiring discovery—for which learning does not rely on the acquisition of rules that can be verbalized (Ashby & Maddox, 2011; Palmer, 2002), such as information integration tasks, prototype-distortion tasks, and unstructured categories (for review, see Ashby & Maddox, 2011; Seger & Miller 2010).

The category learning literature is vast and is important to consider in a research program dedicated to aphasia—the loss of language most frequently associated with stroke, traumatic brain injury, or progressive neurological disease—particularly because research has shown that neurological damage affects categorization and category learning ability. Individuals with Parkinson's disease (PD) and individuals with amnesia show facilitated learning under certain task conditions over others (Knowlton, Mangels, & Squire, 1996; Knowlton, Squire, & Gluck, 1994; Shohamy, Myers, Grossman, et al., 2004; Swainson et al., 2000). When compared with control participants, these populations also show differences in the strategies used to approach learning.

Questions about abstract category learning have been sparse in the literature on aphasia, as, until recently, the focus in aphasia was specifically on language and its organization, formulation, and retrieval. Most of the research on learning in aphasia focuses on novel word learning

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(Freedman & Martin, 2001; Grossman & Carey, 1987; Kelly & Armstrong, 2009; Tuomiranta et al., 2011), word–picture/word–object association learning (Breitenstein, Kamping, Jansen, Schomacher, & Knecht, 2004; Glass, Gazzaniga, & Premack, 1973; Marshall, Neuburger, & Phillips, 1992), or artificial grammar learning (Christiansen, Louise Kelly, Shillcock, & Greenfield, 2010; Floel, de Vries, Scholz, Breitenstein, & Johansen-Berg, 2009). These studies are critically important, as they have helped us to understand that participants with aphasia (PWA) are capable of new verbal learning. In addition, studies have confirmed a relationship between behaviors observed during novel word learning and domain specific deficits in aphasia measured through standardized assessments. What remains unanswered and nondissociable in these studies, however, is an understanding of learning in aphasia that is not so heavily laden with language. We are increasingly understanding that language cannot be dissociated from nonlinguistic factors such as attention and executive control (see Cahana-Amitay & Albert, 2014). Nonlinguistic learning remains an important and underexplored topic in aphasia.

Recently, in a first exploration into nonlinguistic probabilistic category learning in aphasia, Vallila-Rohter and Kiran (2013) probed the learning ability of PWA using a prototype-learning task. The task involved multidimensional abstract animal stimuli with multiple features. Two categories were established along a continuum, and category membership was determined by the percentage of feature overlap with each of two prototypes. Successful learning corresponded with categorization scores that matched the percentage of feature overlap with each prototype. In this study, only 11 out of 19 PWA were found to successfully learn categories. In contrast, all healthy age-matched control participants learned to correctly categorize animals. Performance by PWA was not predicted by severity of aphasia, further suggesting that language and learning networks may be differentially affected by aphasia-inducing strokes. These results were the first indication that impairments in the categorical learning of abstract feature representations may often occur in stroke aphasia.

Because some PWA were able to learn successfully, whereas others were not, the next step is to look beyond overall accuracy rates to the process of learning. Can an understanding of the strategies engaged to approach these tasks shed light on different presentations of learning success in aphasia? Prior research suggests that it can, as strategy analyses have provided insights beyond those brought about through accuracy analyses alone.

Gluck, Shohamy, and Myers (2002) pioneered this type of strategy analysis work, exploring how participants went about performing the weather prediction task (WPT; Knowlton et al., 1994). The WPT is a protocol in which participants gradually learn to predict one of two outcomes—sunshine or rainy weather—on the basis of a presentation of cards. Stimuli for the WPT are four unique stimulus cards composed of geometric shapes. On each trial, one to three cards are presented, and participants are instructed to guess whether each card combination predicts sunshine or rainy weather. Individual cards are probabilistically associated with one outcome or another, such that successful learning of the task is achieved through gradual, trial-by-trial learning influenced by the statistical nature of weather–card associations.

In the first phase of their study, Gluck et al. (2002) collected qualitative data in the form of open-ended and multiple-choice questions aimed at identifying how participants approached learning. Researchers noted that consistent patterns arose among responses and termed these *strategies*: one-cue strategies, multi-cue strategies, and singleton strategies. One-cue learners developed rules on the basis of the presence or absence of single cards (e.g., predicting rain whenever the triangle cue card appeared with or without other cue cards). Multi-cue learners reported attending to a combination of cards (e.g., predicting rain whenever a triangle card appeared with a diamond card). Singleton learners devised response rules only when single cards appeared (e.g., predicting rain when the triangle cue card appeared alone), guessing on remaining trials. Researchers used these qualitative data to establish quantitative models predicting the response patterns that would arise when implementing each approach.

Models were based on the assumption that to successfully learn probabilistic learning tasks, participants must produce a fairly constant pattern of responses that is resistant to negative feedback, because feedback on an individual trial is not always reliable (i.e., a pattern will be reinforced as belonging to one category on 80% of trials and as belonging to the opposite category on 20% of trials). Learning of these tasks is experience-based and depends on accrued information over multiple trials. Although the researchers acknowledged that the approaches described and modeled in the study do not suffice to characterize all of the possible strategies used when completing this task, the majority of participant response profiles averaged over 200 trials fit ideal data. Follow-up analyses of responses over 50 trial blocks also provided good fits to model data. An evaluation of the fit between results and modeled strategies, therefore, establishes a metric of how learning is carried out, and it provides insights into participants' approaches to the task that extend beyond overall accuracy scores.

The findings established by Gluck et al. (2002) set the stage for further examinations into strategy use in individuals with PD or amnesia that are relevant when considering aphasia. Meeter, Myers, Shohamy, Hopkins, and Gluck (2006) conducted strategy analyses over data collected from healthy control participants and participants with amnesia completing probabilistic learning tasks. In this study, a final "strategy"—the random pattern (RP), or no strategy—was introduced. The random strategy models behavior closest to chance performance. When introducing this model, Meeter et al. noted that behavior that most closely matches a random strategy could correspond to RPs, switching strategies, or probabilistic rules not captured by other models. The inclusion of a random strategy into analyses was beneficial, as it helps reduce the number of falsely identified one-cue and multi-cue strategy fits.

Meeter et al. (2006) observed a switch from simple to complex strategies in control participants—a progression that suggests an ability to integrate information and feedback over the course of learning. In comparison, most patients with amnesia implemented no strategy during learning. Intermittent strategy use and strategy switches were observed among patient data, but these were not constructive, often involving switching from simple or intermediate strategies to less optimal strategies or no strategy and back. Such patterns led to poor overall learning and are consistent with memory impairments and a difficulty tracking feedback or recalling attempted strategies. The inclusion of a strategy analysis in this study shed light on the processes that led to different accuracy rates between groups in later phases of classification.

Similarly, Shohamy, Myers, Grossman, et al. (2004) examined strategy use on the WPT, this time comparing the performance of healthy individuals with that of patients with PD. Again, control participants were observed to use multi-cue strategies over time. Patients with PD showed improved accuracy over 3 days of data collection; however, strategies remained simple and focused on single cues. Findings highlight the importance of analyses at the strategy level because patients with PD showed overall accuracy scores comparable with those of control participants by the final day of testing but continued to approach tasks in a distinct manner.

As mentioned above, in aphasia very little remains known about nonlinguistic learning. However, many of the factors thought to contribute to reduced learning of probabilistic tasks in PD and amnesia (e.g., reduced memory ability, reduced attention, executive control, and reduced feedback ability) have been identified as areas of weakness for PWA as well (Caspari, Parkinson, LaPointe, & Katz, 1998; Christensen & Wright, 2010; Glosser & Goodglass, 1990; Kalbe, Reinhold, Brand, Markowitsch, & Kessler, 2005; Murray, 2012; Murray, Ramage, & Hopper, 2001; Seniow, Litwin, & Lesniak, 2009). In an interesting study comparing errorless and errorful anomia treatment methods, Fillingham, Sage, and Lambon Ralph (2006) found that, irrespective of treatment type, therapy outcomes were significantly correlated with measures of recognition memory, executive function, and monitoring skills but not with language measures. Cognitive skills that support learning, feedback processing, and integration were critical to therapy, independent of language measures. PWA may vary in their ability to monitor feedback and effectively develop strategies through the course of learning—an important consideration for therapy.

As a first step toward answering these questions, we explore strategy use on a probabilistic category learning task that, like the WPT, engages participants in experienced-based gradual learning. Through exposure, participants learn to group perceptual stimuli on the basis of shared physical features and/or similarly paired outcomes. First, we examine the overall learning success of control participants without aphasia and PWA as they complete a nonlinguistic category learning task. Second, we examine the strategies implemented by both groups in training and testing phases of our task to probe strategy evolution. We apply an adaptation of Gluck et al.'s (2002) and Meeter et al.'s (2006) mathematical models to determine whether individuals use an optimal multi-cue (OMC) strategy, various single feature (SF) strategies, or an RP during classification and training phases.

On the basis of results obtained in Vallila-Rohter and Kiran's (2013) study, we expect control participants to learn categories successfully, whereas we expect PWA to present variable success in learning. Prior research suggests that severity of aphasia will not predict which PWA successfully learn categories. We hypothesize that, like individuals with PD and individuals with amnesia, PWA will utilize complex strategies less frequently than healthy control participants, predominantly engaging SF strategies. Deficits of attention, executive function, and memory present in aphasia are likely to affect the rapid development of complex multi-cue strategies. PWA do not have the dense memory impairments observed in amnesia, so RP strategy profiles are not expected.

Method

Participants

Fifty-three English speaking PWA (30 men, 23 women) —who previously had a left hemisphere stroke or hemorrhage and who ranged in age from 28.4 to 87 years (M = 60.8, SD = 12.8)—participated in the study. PWA were tested outside of the acute period, at least 6 months after the onset of their stroke (M = 51.3, SD = 49.6). All PWA were premorbidly right handed. Medical records were obtained to confirm the location of the cerebrovascular accident and are presented in Table 1. We were not able to obtain records for eight PWA. PWA completed an average of 15.4 years of education (SD = 3.1). Severity of aphasia, as determined by aphasia quotients (AQs) computed from the Western Aphasia Battery (WAB; Kertesz, 1982), ranged from 10.2 to 100 (M = 72.8, SD = 23.9). Though some of these AQs are not traditionally classified as aphasic, high-level individuals were included in the current study, as we are interested in comprehensively representing the disorder by including a wide variety of patients. We have measures on other linguistic tests outside the scope of this article that demonstrate the presence of aphasia (see online supplemental materials, Supplemental Table 1). As determined by the WAB, aphasia types included global aphasia, Broca's aphasia, Wernicke's aphasia, conduction aphasia, transcortical motor aphasia, and anomic aphasia. The cognitive–linguistic abilities of PWA were tested using the Cognitive Linguistic Quick Test (CLQT; Helm-Estabrooks, 2001). Three PWA dropped out of the study prior to fully completing our diagnostic battery and, therefore, are missing measures of cognitive–linguistic ability (one participant) or are not assigned an aphasia type (two participants).

A group of 12 English speaking control participants without aphasia (four men) completed the experiment. The age of these individuals ranged from 32.9 to 72.6 years (M = 61.3, SD = 10.1; see Table 2). Control participants

Table 1. Characteristics of participants with aphasia (PWA).

Participant	Gender	Age (years)	Education (years)	MPO	Aphasia type	AQ	Attn	Mem	Exec	VS	Lesion information
PWA1	M	52	11	260	Anomic	61	54	96	21	52	L MCA CVA
PWA2	M	53	16	48	Wernicke's	58	125	108	11	57	
PWA3	F	63	16	65	Anomic	69	194	139	19	92	L MCA with BG involvement
PWA4	M	61	13	6	Anomic	91	167	145	15	72	L MCA CVA
PWA5	M	46	16	86	Broca's	73	195	118	30	99	L MCA CVA
PWA6	F	57	16	68	Anomic	80	132	118	7	43	L MCA with BG involvement
PWA7	M	72	18	15	Wernicke's	77	173	132	21	83	L MCA CVA
PWA8	M	61	16	45		68	199	157	22	94	L MCA CVA
PWA9	M	68	19	13	Anomic	74	142	136	19	73	L MCA CVA
PWA10	M	76	3	15			142	102	8	55	L MCA CVA
PWA11	M	53	16	24	Anomic	91	72	113	23	56	L PCA CVA
PWA12	F	73	19	136	Anomic	91	46	142	16	32	L MCA CVA
PWA13	M	66	12	15	Anomic	97	200	142	29	101	L MCA CVA
PWA14	F	74	12	14	Transcortical motor	51	38	113	14	38	L ACA/MCA CVA
PWA15	F	55	12	10	Anomic	85	192	152	26	88	L MCA with BG involvement
PWA16	M	75	16	17	Transcortical motor	83	144	114	10	62	L ACA/posterior MCA CVA
PWA17	F	28	18	23	Conduction	87	202	156	30	100	L MCA CVA
PWA18	F	59	16	48	Conduction or anomic	74	131	113	6	52	
PWA19	M	50	12	32	Anomic	86	186	138	26	93	L MCA with BG involvement
PWA20	M	58	16	29	Wernicke's/conduction	60	49	105	12	38	
PWA21	M	82	12	9	Conduction	72	164	120	16	74	L MCA CVA
PWA22	F	87	16	130	Anomic	97	190	156	29	94	L MCA with BG involvement
PWA23	F	68	12	28	Transcortical motor	82	110	89	17	35	L MCA CVA
PWA24	M	68	17	21	Anomic	95	192	155	28	97	L MCA CVA
PWA25	M	58	16	9	Anomic	97	160	147	25	77	
PWA26	M	49	12	162	Broca's	58	163	98	19	74	L MCA CVA
PWA27	F	66	18	42	Broca's	31	101	40	3	39	L MCA with BG involvement
PWA28	F	83	16	39	Anomic	93	172	145	22	79	L MCA CVA
PWA29	F	66	18	84	Conduction	70	184	120	20	88	L MCA CVA
PWA30	M	70	12	76	Global	10	13	30	3	17	L MCA with BG involvement
PWA31	F	64	18	18	Anomic	68	146	102	14	71	
PWA32	F	49	14	31	Broca's	21	177	47	25	88	L MCA CVA
PWA33	F	66		34	Anomic/conduction	78	196	136	27	98	L MCA CVA
PWA34	F	55		28	Anomic	83	77	156	21	57	L MCA CVA
PWA35	F	29	18	75	Anomic	93	203	159	30	95	L MCA CVA
PWA36	M	56	16	13	Anomic	87	196	150	26	96	L MCA CVA
PWA37	M	60	19	27	Anomic	83	190	132	25	91	L MCA CVA
PWA38	M	44	12	12	Anomic	96	196	151	27	96	L MCA with BG involvement
PWA39	M	66	16	123	Anomic	86					
PWA40	M	65	19	24	Anomic	98	187	163	22	81	L MCA CVA
PWA41	F	38	16	53	Anomic	78	173	139	22	77	L MCA/ACA CVA
PWA42	M	65	16	120	Conduction/Wernicke's	23	197	93	28	101	
PWA43	M	53	16	107	Conduction/Wernicke's	48	178	93	24	92	L MCA/ACA CVA
PWA44	M	69	14	17	Anomic	100	201	149	30	91	L MCA CVA
PWA45	F	77	16	94	Anomic	98	206	183	29	86	L MCA CVA
PWA46	M	69	19	109	Anomic	80	137	115	18	65	

(*table continues*)

Table 1 *(Continued).*

Participant	Gender	Age (years)	Education (years)	MPO	Aphasia type	AQ	Attn	Mem	Exec	VS	Lesion information
PWA47	F	53	12	25	Wernicke’s	41	144	74	17	64	L MCA with BG involvement
PWA48	M	59	18	110	Conduction	78	194	156	40	92	L MCA CVA
PWA49	M	70	21	28	Conduction/Wernicke’s	34	167	66	23	91	L MCA CVA
PWA50	F	60	16	70	Anomic	99	209	175	32	101	L MCA CVA
PWA51	F	34	14	6	Wernicke’s	25	184	66	18	92	L MCA CVA
PWA52	M	79		7	Broca’s	28	184	42	22	84	L MCA CVA
PWA53	F	50	18	24	Anomic	94	210	181	31	100	L MCA CVA

Note. MPO = months post onset of cerebrovascular accident (CVA). Composite scores of attention (Attn), memory (Mem), executive functions (Exec), and visuospatial skills (VS) as obtained with the Cognitive Linguistic Quick Test—as well aphasia quotients (AQs) as measured by the Western Aphasia Battery—are reflected. For participants 18–69 years of age, scores on the Cognitive Linguistic Quick Test are classified by severity as follows: Attn: within normal limits (WNL) = 180–215, mild = 125–179, moderate = 50–124, severe = 0–49; Mem: WNL = 155–185, mild = 141–154, moderate = 110–140, severe = 0–109; Exec: WNL = 24–40, mild = 20–23, moderate = 16–19, severe = 0–15; VS: WNL = 82–105, mild = 52–81, moderate = 42–51, severe = 0–41. Under lesion information, we indicate those PWA with confirmed basal ganglia (BG) involvement. M = male; F = female; MCA = middle cerebral artery; ACA = anterior cerebral artery; PCA = posterior cerebral artery.

Table 2. Characteristics of control (Cn) participants.

Cn participant	Cn1	Cn2	Cn3	Cn4	Cn5	Cn6	Cn7	Cn8	Cn9	Cn10	Cn11	Cn12
Gender	F	M	F	M	M	F	F	F	M	F	F	F
Age (years)	57	61	33	55	70	65	57	58	69	61	60	73
Education (years)	16	21	19	18	16	12	16	18	16	16	16	16

were matched to the average years of education of the PWA (M = 16.7, SD = 2.2). Control participants had no known history of neurological disease or developmental disabilities. One control participant was left-handed. Participants were recruited from the Boston area and were tested at the Sargent College of Rehabilitation Sciences.

Learning Task

Stimuli for the learning task were two sets of 1,024 fictional animals, which were introduced by Reed, Squire, Patalano, Smith, and Jonides (1999); updated by Zeithamova, Maddox, and Schnyer (2008); and utilized in Vallila-Rohter and Kiran's (2013) study. Animals varied on 10 binary dimensions: color, body shape, body pattern, head direction, ears, feet, leg length, neck length, nose, and tail (see Figure 1). One animal from each set was selected as Prototype A of that set, and the animal that differed from that prototype by all 10 features became Prototype B for each set. Two categories were established in each set. These categories included all animals that shared at least 60% of their features with the prototype within that category, thus including animals sharing 90%, 80%, 70%, and 60% of their features, respectively, with category prototypes. Note that because of the binary nature of features, these animals shared 10%, 20%, 30%, and 40% of their features, respectively, with the prototypical animal of the opposite category. Each category had an internal structure that was based on the percentage of feature overlap with each of the two prototypes.

Animals are described by their *distance* from Prototype A, animals at Distance 1 being animals that differ from the prototype by one feature (90% overlap), animals at Distance 2 differing from Prototype A by two features (80% overlap), until reaching a distance of 10: Prototype B (see Figure 1). Categorization rates were expected to match the percentage of feature overlap with each prototype. Thus, the percentage of "B" responses increases from 0% to 100% with increasing distance from Prototype A.

The category learning task was computer based and composed of two phases. A 10-min training phase was immediately followed by a 10-min testing phase (see Figure 2). The experiment was programmed using E-Prime 2.0 (Schneider & Zuccolotto, 2002). In training, animals were presented one at a time on a computer screen, and participants were instructed to guess to which of two categories each animal belonged. Responses were indicated with one of two button presses: "1" or "2" corresponding to Categories A and B. Participants were given 4,000 ms to make a response. After a response was made, participants received feedback in the form of a check mark or an "x" for 3,000 ms, indicating whether their response was correct or incorrect. Participants were told that they would initially be guessing at random but that eventually they would start to recognize animals as belonging to one category or to another. Accuracy percentage was reflected on a small counter in the upper right hand corner of the screen. Participants were instructed to attend to all features.

During the training phase, participants completed 60 learning trials comprising three repetitions of 20 animals within each category. Prototypical animals were never shown in training. Each feature appeared 30 times. Features of Prototypical Animal A were seen on animals categorized in Category A for 70%–80% of trials (21–24 times). Features of the opposite prototype, Prototypical Animal B, were only seen on animals categorized as Category A members on 20%–30% of trials (6–9 times).

Following training, participants completed 67 classification trials in a testing phase with no feedback. Participants were given 4,000 ms to categorize each animal. In the testing phase, participants were tested on 16 animals seen in training and 45 novel category members and prototypes. Testing included 56 animals at Distances 1–4 and Distances 6–9. Five midline animals (Distance 5) were presented. For the purposes of analyses, these were coded with a correct "A" response and were expected to lead to an average percentage "B" response (%BResp) around 50%.

Stimulus sets (Set 1 and Set 2) were counterbalanced across participants. Data were collected on reaction time and accuracy; however, only the accuracy of responses was analyzed for the current article. Strategy analyses were conducted over training and testing phases allowing for an examination of the strategy progression from training to testing. Note that in the testing phase, participants no longer received feedback regarding the accuracy of their responses.

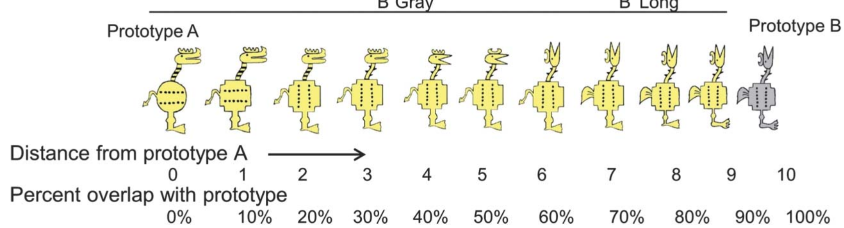
Data Analyses

Accuracy Rates and Learning Score

Each participant was first assigned a score of learning. To achieve this, all individual participant results were analyzed by the percentage of B responses as a function of distance from Prototype A. Scores at each distance were first converted into a %BResp score. As control participants have a tendency to probability match during this type of learning (see Knowlton et al., 1994), %BResp scores were expected to incrementally increase by a factor of 10% from 0% to 100% (from Distance 0 to Distance 10). Thus, learning corresponds to a linearly increasing %BResp with a slope of 10. Chance responses would produce a linear slope of zero (%BResp = 50% at each distance). Learning

Figure 1. Presentation of features (Dimensions A and B) for Stimulus Sets 1 and 2. Animal pictures are a representative sample of stimuli at Distances 1–10 from Prototype A that differ from Prototypical Animal A by 1–10 features. Distance from Prototype A is identified as well as the percentage of feature overlap with Prototype B.

Feature	Animal set 1		Animal set 2	
1	Neck length	A Round B Square	Body shape	A Short B Long
2	Tail	A Horizontal B Vertical	Body pattern	A Straight B Curled
3	Feet	A Stripes B Spikes	Neck pattern	A Pointed B rounded
4	Nose	A Horn B Beak	Nose	A Pig B Straight
5	Ears	A Wavy B Scooped	Headpiece	A Straight B Rounded
6	Color	A Forward B Up	Head direction	A Blue B Red
7	Body shape	A Spiked B Fish	Tail	A Square B Rounded
8	Body pattern	A Wide B Thin	Leg width	A Spots B Stripes
9	Head direction	A Duck B Clawed	Feet	A Down B Up
10	Leg length	A Yellow B Gray	Color	A Short B Long



scores from control participants included in this study were calculated in this manner and have been previously reported in Vallila-Rohter and Kiran's (2013) study.

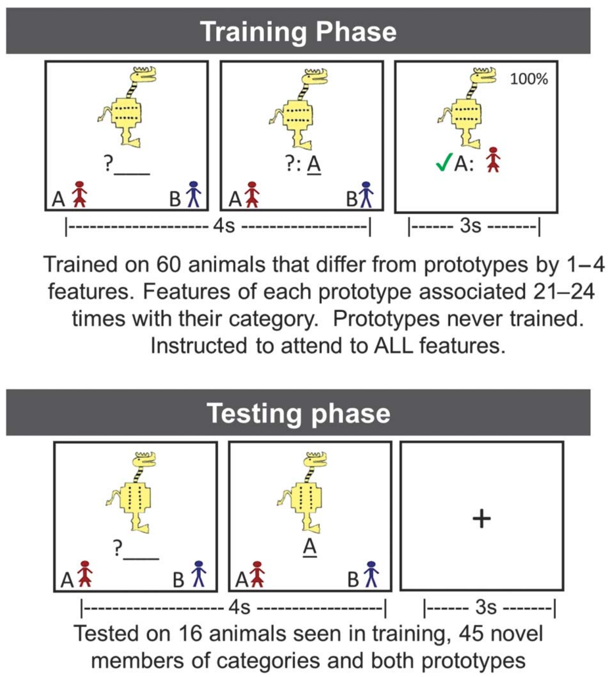
An independent samples *t* test confirmed that there was no significant difference in learning scores achieved on Stimulus Set 1 and Stimulus Set 2, $t(63) = -1.22$, $p = .23$; therefore, data across both stimulus sets were collapsed for all subsequent analyses. Once learning scores were computed, we conducted a one-way analysis of variance (ANOVA) on slope scores of control participants and PWA to examine between-groups differences.

Strategy Analysis

Although scores of learning were determined by examining accuracy rates as a function of distance, strategy analyses examine categorization rates as a function of each individual *feature* value. Animals had 10 features, each with a binary distribution (i.e., body pattern: *spots* or *stripes*); therefore, we examined the %BResp made for each binary option (%BResp when the animal had the feature *spots*; %BResp when the animal had the feature *stripes*).

Next, we set up multiple model strategies adapted to our task and stimuli, on the basis of those models presented by Gluck et al. (2002) and Meeter et al. (2006). To set up models, each feature was coded with a value ranging from 1 to 10, and each binary distribution was coded with a letter A or B (see Figure 1 and Table 3). Neck length, for example, was Feature 1, with a short neck coded as Distribution A, and long neck coded as Distribution B. These correspond to each feature value of Prototypical Animals A and B. The first possible strategy, the OMC strategy, models responses that match the actual "B" reinforcement rate received in training for each dimension of each feature. For the first feature in our experimental set-up, the proportion of correct "B" responses for animals with long necks in training was 0.7. Therefore, the corresponding proportion of correct "B" responses for animals with short necks was 0.3. These proportions are indicated under "OMC" in Table 3. For each feature dimension, the OMC strategy models responses in the testing phase that match the reinforcement rate observed in training. Actual categorization rates that match optimal categorization for multiple features will produce a best fit to the OMC strategy. This strategy is expected to lead to successful scores of learning. Multi-cue strategies are thought to be complex and difficult to verbalize, and they require attending to multiple pattern dimensions at once (Ashby & Ell, 2001). Implementing such a strategy requires attending to, tracking feedback of, and acquiring cue-outcome relationships between multiple pattern dimensions at once.

Figure 2. Representation of experimental training and testing phases.



Next, we established 20 SF strategies, one for each feature dimension.[1] These strategies model behaviors in which participants attend selectively to one particular feature, consistently responding "B" to one feature dimension and "A" to the alternate feature dimension. For example, an individual attending only to the first feature of Stimulus Set 2, body shape, would produce close to a 0% B response to round bodies and close to a 100% B response to square bodies. To account for error, consistent B responses to one feature dimension were set as variable π with a value of 0.95. Response rates to the opposite feature dimension were modeled as $1 - \pi$ (see Meeter et al., 2006). In our SF models, response patterns to all other features are random, corresponding to a proportion of B responses of 0.5 (see Table 3). Successful learning should be possible using SF strategies if participants attend to a particular stimulus dimension and accurately track feedback. These strategies are often described as suboptimal because outcome judgments are based on the value of a single card (Shohamy, Myers, Onlaor, et al., 2004). SF strategies are simple strategies that require feedback tracking and integration but without the additional working memory or attentional loads of integrating and tracking feedback across multiple features at once.

[1]SF strategies are based on one-cue strategies modeled in prior studies and described in the introduction, but these strategies are renamed because they reflect an adaptation specific to our category learning task.

Finally, we included a random strategy as proposed by Meeter et al. (2006). A random strategy is modeled as a 50% B response rate to each feature dimension and, as noted previously, can represent random behavior, no strategy, or a multitude of strategies that deviate from those already modeled (OMC and SF in our study). Including a random model in analyses helps reduce the number of falsely identified SF and multi-cue strategy fits (see Meeter et al., 2006). Under stringent error criteria (π), such as 0.95, the range of responses fit by a random strategy is wide. In the current study, we label this range and strategy fit as RP. We model this strategy to improve our identification of SF and multi-cue strategy fits, but we do not expect many of our participants to produce results fitting an RP.

Finally, we adapted the quantitative methods proposed by Gluck et al. (2002) to quantify the fit of each participant's responses with each of our models. We used the following calculation to assign each participant with a fit score for each model:

$$Score\ for\ Model\ M = \frac{\sum_F \left(\#B\_expected_{F,M} - \#B\_actual_F\right)^2}{\sum_F \left(\#Bpresentations_F\right)^2},$$

where F indicates feature (10 features, each with a binary value); $B\_expected_{F,M}$ indicates the number of times that a B response would be expected for each feature under Model M; $\#B\_actual_F$ indicates the number of B responses made by the participant for each feature; and $\#Bpresentations_F$ indicates the number of times that the feature B appeared in testing. In this manner, we scored each participant's response fit against ideal data expected if participants used an OMC strategy, the 20 SF strategies, or an RP. Each participant was assigned with a fit score between 0 and 1 for each strategy model. The score closest to 0 represented the closest match with ideal model data. Once strategy scores were assigned, an ANOVA was used to examine the relationship between slope scores of learning and strategy use. We used chi-square analyses to examine and compare the distribution of RP, SF, and OMC users in each group and across groups.

Results

Learning Results and Strategy Use

Learning Scores

We first conducted an ANOVA on scores of learning to examine whether differences arose between overall slope scores of learning between control participants and PWA. As expected, slope scores of learning were significantly different between PWA and control participants without aphasia, $F(1, 63) = 5.10$, $p = .03$. The mean slope score of learning for PWA was 3.2 ($SD = 5.2$). The mean slope score of learning for the control group was 6.8 ($SD = 4.1$), closer to ideal learning slopes of +10. See online supplemental materials, Supplemental Table 2, for slope scores for all participants.

Table 3. Set-up of model strategies.

Feature		% B response rate in training	OMC	RP	SF-1A	SF-1B	SF-2A	SF-2B	SF-3A	SF-3B	SF-4A	SF-4B	SF-5A	SF-5B	SF-6A	SF-6B	SF-7A	SF-7B	SF-8A	SF-8B	SF-9A	SF-9B	SF-10A	SF-10B
1	A	30	0.3	0.5	π	$1-\pi$	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
	B	70	0.7	0.5	$1-\pi$	π	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
2	A	20	0.2	0.5	0.5	0.5	π	$1-\pi$	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
	B	80	0.8	0.5	0.5	0.5	$1-\pi$	π	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
3	A	30	0.3	0.5	0.5	0.5	0.5	0.5	π	$1-\pi$	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
	B	70	0.7	0.5	0.5	0.5	0.5	0.5	$1-\pi$	π	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
4	A	20	0.2	0.5	0.5	0.5	0.5	0.5	0.5	0.5	π	$1-\pi$	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
	B	80	0.8	0.5	0.5	0.5	0.5	0.5	0.5	0.5	$1-\pi$	π	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
5	A	20	0.2	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	π	$1-\pi$	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
	B	80	0.8	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	$1-\pi$	π	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
6	A	20	0.2	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	π	$1-\pi$	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
	B	80	0.8	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	$1-\pi$	π	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
7	A	30	0.3	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	π	$1-\pi$	0.5	0.5	0.5	0.5	0.5	0.5
	B	70	0.7	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	$1-\pi$	π	0.5	0.5	0.5	0.5	0.5	0.5
8	A	20	0.2	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	π	$1-\pi$	0.5	0.5	0.5	0.5
	B	80	0.8	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	$1-\pi$	π	0.5	0.5	0.5	0.5
9	A	30	0.3	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	π	$1-\pi$	0.5	0.5
	B	70	0.7	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	$1-\pi$	π	0.5	0.5
10	A	30	0.3	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	π	$1-\pi$
	B	70	0.7	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	$1-\pi$	π

Note. Parameter π was set to 0.95. OMC = optimal multi-cue; RP = random pattern; SF = single feature.

Strategy Analyses

Next, we conducted two sets of strategy analyses for each participant, one over the training phase and a second over the testing phase of categorization. Strategy analyses over data from control participants and PWA demonstrated that all results from training and testing phases could be fit with modeled strategies with a tolerance level of 0.15, with the exception of testing phase data for one patient participant, PWA20. Data from this participant were dropped from subsequent analyses. See online supplemental materials, Supplemental Table 2, for model fit scores for all participants. We performed chi-square analyses to determine whether any differences arose between PWA and control participants in the types of strategies utilized over the two experimental phases. Strategy use was significantly different across groups in the training phase of the experiment, $\chi^2(2) = 5.87$, $p = .05$. A larger proportion of PWA used RP strategies in training than did control participants (0.67 and 0.50, respectively). Control participants demonstrated a larger proportion of OMC strategy use than PWA (0.33 and 0.08, respectively; see Figure 3).

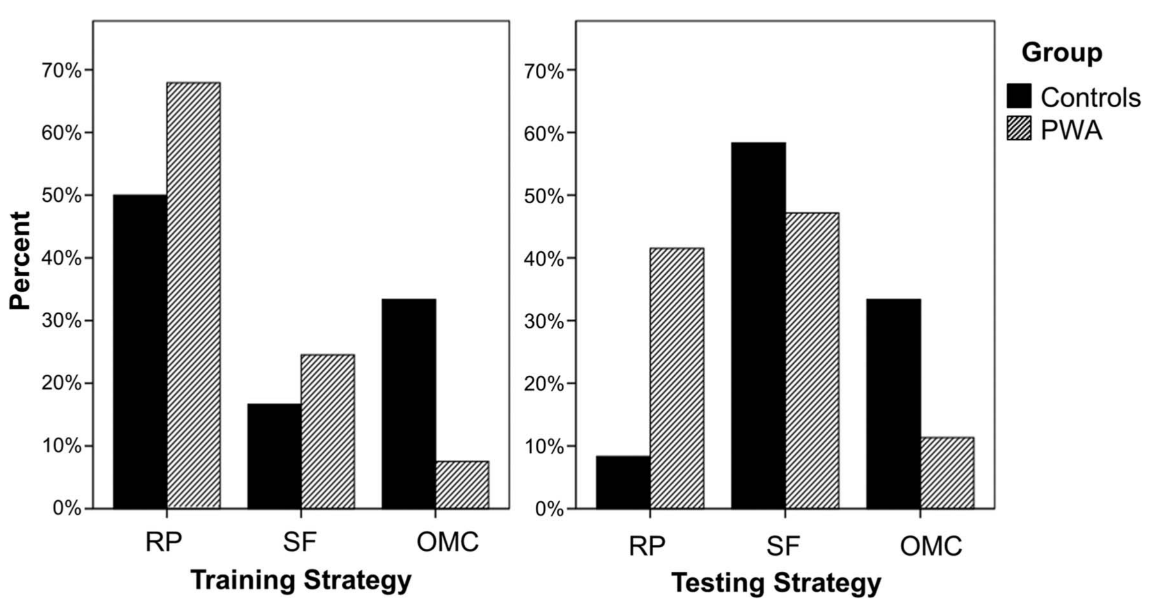
Strategy use was also significantly different across groups in testing phases, $\chi^2(2) = 6.08$, $p = .05$. By testing phases, the proportion of RP strategy use for control participants was only 0.08 compared with 0.40 for PWA. Control participants showed a higher proportion of OMC strategy use than did PWA (0.33 and 0.11, respectively). Thus, PWA were observed to have a relatively high use of RP strategies in training and testing phases, which was not observed in control participants. Few PWA developed complex OMC strategies.

Four control participants rapidly developed SF or OMC strategies in training phases that they maintained into testing phases. Six control participants were observed to progress from either no strategy in training (RP) to an SF or OMC strategy in testing. Among our PWA, 13 rapidly developed SF or OMC strategies in training that they maintained or optimized in testing phases. Twenty-one PWA (40%; PWA1–PWA22, PWA20 was dropped from these analyses) were never observed to develop a strategy (see online supplemental materials, Supplemental Table 2).

Learning as a Function of Strategy Use

We were next interested in examining the relationship between strategy use and success with learning. To do this, we first conducted an ANOVA to compare slope scores of learning following RP, SF, and OMC strategy use in training. Results were significant, $F(2, 61) = 10.84$, $p < .001$, indicating that there was a difference between slope scores for the three types of strategy use. Tukey's post hoc analyses revealed that the slope scores of learning were significantly different between participants using RP and SF strategies in training ($p = .001$; RP slope scores: $M = 1.9$, $SD = 5.1$; SF slope scores: $M = 7.2$, $SD = 3.2$) as well as between participants using RP and OMC strategies in training ($p = .004$; OMC slope scores: $M = 7.8$, $SD = 2.4$). Slope scores following RP strategy use were significantly lower in both cases. Slope scores following SF and OMC strategy use in training were not significantly different ($p = .95$). Thus, those participants who were able to rapidly engage SF or OMC

Figure 3. Significant differences arise in the strategy use of control participants and participants with aphasia (PWA) in training and testing phases. PWA have a higher reliance on random patterns (RPs) in both phases. Whereas control participants shift to a high reliance on single feature (SF) and optimal multi-cue (OMC) strategies in testing, PWA continue to show frequent RP use in testing. Few PWA develop OMC strategies.



strategies in training produced higher overall learning scores in testing phases.

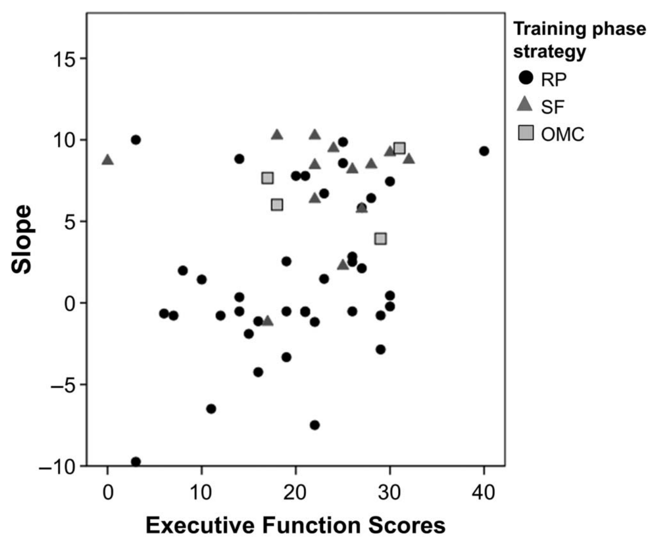
Examining the relationship between learning and strategy use in *testing*, a one-way ANOVA again revealed significant differences, $F(2, 61) = 21.11$, $p < .001$. Tukey's post hoc analyses again revealed that slope scores of learning were significantly different between participants using RP and SF strategies ($p < .001$; RP slope scores: $M = -0.2$, $SD = 2.2$; SF slope scores: $M = 5.1$, $SD = 5.3$) and between participants using RP and OMC strategies in testing ($p < .001$; OMC slope scores: $M = 9.2$, $SD = 1.4$). Lowest slope scores were again achieved under instances of RP strategy use. The difference in slope between SF and OMC strategy use was significant ($p = .02$), with OMC strategy use leading to significantly higher slope scores. Thus, to produce the highest categorization scores in testing, participants had to apply OMC strategies. SF strategies led to the next highest categorization scores. Final slope scores of learning were lowest for those individuals who did not develop strategies in training or testing, producing data that best fit an RP.

Examining the Relationship Between Patient Characteristics, Overall Learning, and Strategy Use

To examine the relationship between learning, strategy use, and cognitive–linguistic factors, we conducted two sets of partial correlations between slope and AQ, attention, executive function, memory, and visuospatial skills—one controlling for strategy used in training, and one controlling for strategy used in testing. The partial correlation between slope score and executive function, controlling for strategy group in training, was significant, $r(48) = .40$, $p < .01$, demonstrating that patients with higher slopes of learning also have higher scores of executive function when controlling for strategy type in training. Visual inspection of the data (see Figure 4) reveals a relatively broad range of executive function scores across participants, with ideal learning slopes close to +10. What is most notable is a small cluster of PWA with the lowest executive function scores on the CLQT (<18) who all fall into the RP strategy group. The partial correlation between slope score and visuospatial skills, controlling for strategy in training, was also significant, $r(48) = .34$, $p = .02$. Overall, those PWA with the greatest impairment in visuospatial skills (lower scores on the CLQT) produced poor scores of learning and implemented RP or SF strategies. Many patients with only mild or no impairment in visuospatial skills, however, produced similarly low scores of learning and utilized RP and SF strategies. The remaining partial correlations between slope score and AQ, attention, and memory (controlling for strategy type in training) were nonsignificant: AQ, $r(47) = -.17$, $p = .25$; attention, $r(47) = .23$, $p = .12$; and memory, $r(47) = -.02$, $p = .87$.

Similarly, the partial correlation between slope score and executive function, controlling for strategy group in testing, was significant, $r(47) = .33$, $p = .02$. None of the remaining partial correlations controlling for strategy group in testing were significant: AQ, $r(47) = -.06$, $p = .69$; visuospatial skills, $r(47) = .24$, $p = .09$; attention, $r(47) = .16$, $p = .29$; and memory, $r(47) = .05$, $p = .71$.

Figure 4. Scatter plot of executive function scores and learning slope separated by strategy use in training. Note that participants with aphasia with high scores of learning near +10 and low scores of learning near zero have a wide range of executive function scores. A small cluster of individuals with the lowest executive function scores, however, all fall into the random pattern (RP) strategy group. SF = single feature; OMC = optimal multi-cue.



On the basis of the lesion information obtained for each patient from medical records, we were able to identify those patients with confirmed basal ganglia involvement. Because basal ganglia structures have been implicated in successful probabilistic learning, we were interested in determining whether PWA who never developed strategies were those with lesions involving the basal ganglia. Five of the 21 PWA who never developed strategies (who instead used RPs in training and in testing) had lesions involving the basal ganglia. Four PWA with basal ganglia involvement developed SF or OMC strategies by testing.

Discussion

In this study, we aimed to explore strategy use in PWA compared with control participants as they completed a feedback-based probabilistic category learning task. As expected, we found differences in the overall learning success of PWA compared with control participants. Similarly, differences arose between groups in the strategies implemented in each phase of the experiment: training and testing.

As predicted, PWA had significantly lower categorization scores than control participants without aphasia. This is consistent with prior research that demonstrated lower rates of successful category learning in PWA compared with control participants (Vallila-Rohter & Kiran, 2013). Consistent with prior studies, comparisons between strategy use and learning success showed that the development of either SF or OMC strategies was critical for successful categorization in testing (Gluck et al., 2002; Hopkins, Myers, Shohamy, Grossman, & Gluck, 2004; Knowlton et al., 1994; Rustemeier, Schwabe, & Bellebaum, 2013; Shohamy, Myers, Grossman, et al., 2004; Shohamy, Myers, Onlaor, et al., 2004). Successful learning following OMC strategies is not surprising, as this reflects that through the course of training, participants learned to produce responses that closely matched the actual reinforcement rate of multiple animal features. OMC strategy implementation requires individuals to attend to multiple features at once, accurately tracking and accruing feedback information through the course of learning. To obtain successful categorization rates using SF strategies, participants must identify a feature with a high reinforcement rate in training and implement this strategy in testing phases.

In contrast to OMC and SF strategies that led to successful learning, no participant implementing an RP in testing had good categorization rates. Recall that the RP strategy models behavior closest to chance performance and may correspond to RPs or to frequent strategy switches. Current results confirm that the nature of the task required participants to develop strategies on the basis of accrued feedback to succeed with learning. Hypothesis testing, tracking, and monitoring appear to be critical to learning, whether they were conscious or unconscious. Furthermore, participants had to develop a strategy resistant to instances of negative feedback. Because participants are unlikely to make responses that are completely random, we hypothesize that many participants with results that fit an RP model modified their responses on the basis of prior stimuli on each trial. Constant strategy switches would produce results with insufficient consistency to match modeled strategies or to produce scores of successful categorization.

Strategy use was significantly different across groups, with control participants more consistently and more rapidly developing suboptimal and optimal SF and OMC strategies than PWA. Half of our control participants were able to rapidly develop strategies in testing that they either maintained or optimized by testing phases. The remaining control participants took longer to develop strategies, eventually implementing SF or OMC strategies by testing phases. Only one control participant showed an inferior progression from an SF strategy to no strategy.

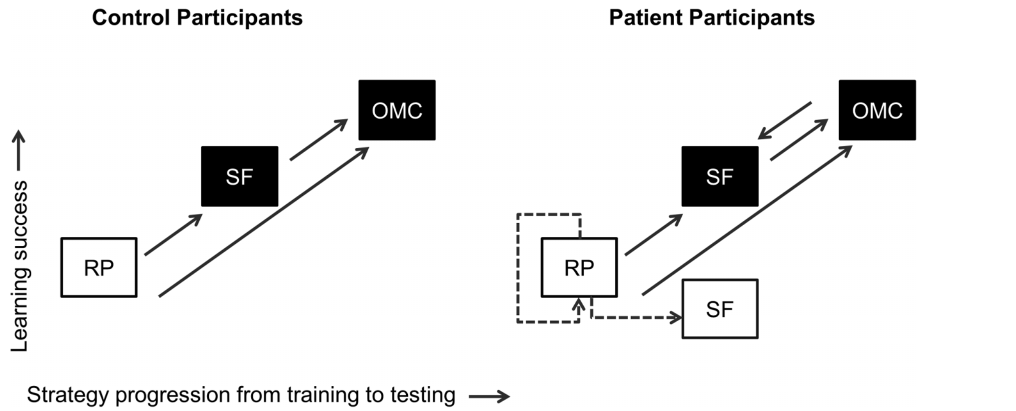
For PWA, three major profiles exist: OMC strategy users, SF strategy users, and RP strategy users (see Figure 5). First, 11.5% of PWA, a small subset, were able to implement OMC strategies in testing phases and to successfully categorize animals. Although prior studies in patients with amnesia and with PD did not see OMC strategy use (Hopkins et al., 2004; Meeter, Radics, Myers, Gluck, & Hopkins, 2008; Shohamy, Myers, Kalanithi, & Gluck, 2008; Shohamy, Myers, Onlaor, et al., 2004), a small group of PWA evidenced preserved abilities to rapidly develop complex, multidimensional strategies. Results demonstrate that many PWA likely have neural networks capable of supporting the development of complex strategies to engage in learning of this sort.

Second, 46.2% of PWA implemented SF strategies in testing. On the basis of previous research that showed a gradual progression from singleton cue to multi-cue strategies in learning, we predict that PWA in this subgroup might have progressed to OMC strategies had they completed additional trials. Alternatively, PWA relying on SF strategies may have a limited ability to focus on multiple features at once. This could be the case for participants such as PWA41, PWA42, PWA43, and PWA44 (see online supplemental materials, Supplemental Table 2), who rapidly developed SF strategies, maintained them into testing phases, and produced learning scores close to modeled ideal learning slopes of +10. These PWA were able to develop and maintain SF strategies as well as resist distractors (other features). They were, however, unable to optimize responses based on multiple feature dimensions. Finally, some SF strategy users may have impairments of feedback tracking at the hypothesis testing level. This may be the case for participants who implemented SF strategies in testing but produced scores of learning that were close to chance performance (i.e., PWA26, PWA31, and PWA37; see online supplemental materials, Supplemental Table 2). These PWA focused on an SF but not one with an ideal reinforcement rate. Such PWA demonstrate basic skills of implementing a strategy and selectively attending to features yet appear impaired at the level of feedback response tracking.

Finally, and surprisingly, a third subset—42.3% of PWA tested—never developed strategies and continued to produce an RP of responses through both training and testing phases. This behavior is suggestive of the weakest strategy development systems and produced poor overall category learning in all cases. We hypothesize that PWA in this subgroup have cognitive–linguistic barriers that prevented them from developing strategies. They did not learn to optimize responses or to focus on an SF. We had not expected to see such a high occurrence of RP strategy use in PWA. Recall, however, that participant strategies had to be based on a mental construct robust enough to withstand instances of negative feedback. Because of the probabilistic structure of categories in this task, feedback provided on individual trials was not always reliable. Instead, successful performance depended on information accrued across multiple instances. Thus, participants who constantly modified responses on the basis of immediate antecedents alone did not develop effective strategies. Strategies had to be developed on the basis of responses and feedback accrued over multiple trials.

Meeter et al. (2006) observed such patterns of random responses in individuals with amnesia with dense memory impairments, proposing that deficits in recall of attempted strategies and resulting feedback likely accounted for the observed lack of strategy implementation. Shohamy, Myers, Onlaor, et al. (2004) also observed impaired strategy development in individuals with PD, and they posited that integration, working memory, and strategy switching deficits were to blame. Similar deficits may be present in a subset of PWA. A subset of PWA may also require longer

Figure 5. Schema representing strategy progressing from training to testing in control participants (left panel) and participants with aphasia (PWA; right panel). Solid lines indicate strategy progressions that were observed to lead to successful categorization rates. Dotted lines indicate strategy patterns that did not lead to successful categorization. RP = random pattern; SF = single feature; OMC = optimal multi-cue.



processing times than those included in the present study to develop hypotheses and to track feedback.

We did observe a significant correlation between executive function scores on the CLQT and learning scores when controlling for strategy group. A relationship between learning score and executive function measures had not been seen in previous studies (Vallila-Rohter & Kiran, 2013) but is consistent with the proposal that feedback-based learning requires hypothesis generation, hypothesis testing, and feedback tracking—skills likely to depend on executive functioning abilities. PWA with the lowest scores of executive function were not able to develop strategies in training or in testing. Many PWA who did not develop strategies, however, had a broad range of executive function scores. Thus, cognitive–linguistic barriers preventing strategy development were not identified using the limited battery of assessments examined here. This could be because our cognitive battery was limited. It may also indicate that learning and strategy development represent yet another cognitive construct not yet characterized in the literature. As expected, severity of aphasia did not predict success with learning, providing additional evidence that language and learning networks may differentially be affected in aphasia. This is clinically important, as those patients with the most high-functioning aphasias may not be equipped with robust learning systems. In contrast, some patients with severe degrees of aphasia likely have strong neural networks to support learning.

Many aphasia therapies work toward retraining language through manipulations of auditory and visual stimuli, feedback, and modeling. Currently, we are limited in our understanding of how patients approach such tasks. Are individuals actively integrating feedback and constructing hypotheses related to instruction and cueing? Are patients able to devise strategies to carry over what is learned in therapy into real-world communicative scenarios? These questions, all of which are highly relevant to therapy, require gaining a better understanding of the ways in which PWA process information while engaged in therapy tasks and merit further exploration. Although the current study examined abstract pattern learning—a nontherapy task in a nontherapy environment—individuals who struggled to develop strategies on our task might also have difficulty attending to multiple modalities and integrating feedback in therapy.

Current results highlight the importance of continuing to explore nonlinguistic cognitive factors in aphasia. Here, we replicated the finding of impaired nonlinguistic category learning in a subgroup of PWA. Furthermore, we established that PWA use a variety of strategies when completing these tasks. Surprisingly, a large subset of individuals produced patterns of random responses throughout training and testing, suggestive of impaired strategy development or feedback processing abilities that were not directly reflected in cognitive assessments. Though our battery of cognitive assessments was limited, we hypothesize that learning is a unique metric important to characterize in aphasia. Learning requires dynamic information accrual and integration of feedback—skills not fully captured by static tests of impairment. The most productive classifications of aphasia that may finally lead to individualized therapy will include measures of learning and strategy development ability as well as measures of impairment.

Acknowledgments

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